Research Article

STUDY FOR SYSTEM IDENTIFICATION OF THE BOX CULVERT MODEL WITH AUTOMATED ARTIFICIAL INTELLIGENCE*

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ABSTRACT

Structures are exposed to dynamic effects, but the responses of structures to these effects are mainly calculated with theoretical assumptions. The inadequacy of these theoretical approaches is accepted and criticized by all civil engineering circles. This situation brings with it the search for new solutions. In recent years, experimental methods have become widespread in calculating the responses of structures to dynamic effects. The system identification method is one of these methods. With the system identification method, the mathematical model of the structure system can be obtained. Thus, dynamic parameter estimations give more realistic results. Today, the use of artificial intelligence-neural network is widespread in every field, as well as in the field of system identification. For this reason, in this study, the system identification of the box culvert model was made with the automated artificial intelligence method. As a result of this study, the system identification of box culvert model was made with a success rate of approximately close to one hundred percent. The automated artificial intelligence can provide a very fast andtrue to solve problem in system identification studies. In the light of this study, it is seen that automated artificial intelligence can be used on system identification method in civil engineering field.

Keywords: *System Identification, Automated Artificial Intelligence, Mathematical Model, Neural Network, Box Culvert*

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1.INTRODUCTION

Today, studies and developments about earthquake resistance of structures are very popular. There are many old and new methods used especially when determining the earthquake performance of structures. The methods used in the past century and the beginning of the 21st century have been replaced by newer and more reliable methods. The old methods are generally theoretical and based on some assumptions. The new methods, on the other hand, include more experimental methods and the data represent more real situations. System identification method is one of these methods. System identification (SI) is a modeling process for an unknown system based on a set of input outputs and is used in various engineering fields [1], [2]. With system identification, a mathematical model of the system is created. Effects and reactions on the created model are determined realistically by the mathematical model. In determining the earthquake performance, it is of great importance to obtain the mathematical model of the structure or model correctly. It is known that it is possible to obtain correct earthquake performance only with the correct mathematical model.

The system identification method also includes various improvements. Especially today, the use of artificial intelligence is seen in many areas. In the field of system identification, its use in obtaining parameters and processing data is seen in current academic studies. The authors have many studies [3-19] on system identification and artificial neural network given in the sources. It has been clearly seen that the limits of automated artificial intelligence are pushed by covering various models in these academic studies. Based on all this information, the very up-to-date automated artificial intelligence method was used on system identification in this study. It was decided to choose the box culvert model as the model. Also, it is aimed to interpret the data obtained in the study by sharing it clearly in the results section.

2.AUTOMATED ARTIFICIAL INTELLIGENCE

Automated Artificial Intelligence (AutoAI) is a variant of automated machine learning (AutoML) technology that goes beyond model construction to automate the whole life cycle of a machine learning model. It automates the process of creating predictive machine learning models by preparing data for training, determining the optimum model type for the given data, and selecting the features or columns of data, that best support the problem the model is solving. Finally, as it develops and ranks model-candidate pipelines, automation checks a number of tweaking possibilities to achieve the optimal result. AutoAI defines the requirements and tools to perform such a model selection and tuning work, and provides guidance on the process of building the best set of tools and systems for automating the entire machine learning development lifecycle. This work builds on the automating transformations approach, which enables domain-specific machine learning models to be rapidly developed and deployed into production using specialized, domain-specific or multi-function cloud and on-premises platforms. AutoAI reduces time-to-value and accelerates time-to-insight through. Multi-disciplinary AI architectures that support model building, model tuning, model testing, and model deployment. The concept of multidisciplinary AI has been demonstrated in a variety of domains including the auto industry. AutoAI also proposes a powerful mechanism for specifying and sharing data representation and information about model components. This makes it possible for an enterprise to compose a machine learning system consisting of relatively small chunks of domain-specific machine learning code, which can be optimized to solve very specific problems. Model selection and tuning capabilities, which allow users to share components of their machine learning system, such as parameters, features, and ML models. Model selection and tuning tools can be distributed across a large company, while still allowing consistent tuning and analytics across these components. For example, users can share common ML model architectures (such as neural networks) for predicting goods purchased or miles driven, but can then also share the tuning rules and the data models necessary for identifying the best parameters for this model. In other words, users can build their own machine learning system, but can also freely share their data, architectures, and tuning rules. The new models can then be deployed into production on top of the shared components of the system.

3.MODEL SELECTION

One of the primary challenges for enterprise machine learning models is the selection of data and model architecture. Automated machine learning provides the power to quickly optimize machine learning models for problems that are specific to an organization. AutoAI enables the automated selection and prioritization of a large number of machine learning models for a particular domain, and presents users with a list of models that best fit the requirements of the problem, and may be used to solve that problem. It also provides a set of model options that include existing and new machine learning models, with descriptions and links to public descriptions of those models, to be used to explore their performance. Finally, it highlights metrics associated with each model to be selected, such as accuracy, precision, and predictive accuracy, and provides a visual model selection flow that allows users to rapidly select the best model. AutoAI also features other kinds of model selection and tuning workflows, including models that may need to be pre-trained and evaluated before a data-driven solution can be deployed to solve a problem, and models that may be unqualified by the domain experts that write the use cases, but are suitable for a particular problem and data set. By providing modeling capabilities for the selection of models and tuning of those models, AutoAI reduces the risk of failure in a very risky model development phase.

4.MODEL TUNING

The second primary challenge of most enterprises is tuning a machine learning model. AutoAI's predictive tuning, prediction quality and model quality metrics support a number of pre-built models, and allow users to use it to understand their model performance. AutoAI shows the signal-to-noise ratio of any model at any time, with a highly graphical and informative display, and it provides measurements for modeling quality and metrics for the predictive performance of a model. AutoAI enables users to see where there are performance issues, provide feedback for further tuning, and identify outliers that may need to be fixed. AutoAI can also provide the flexibility to use their own (in-house) models, which can then be used as is, or to apply them in a flexible way to the problem, and tune them based on the needs and the domain. For example, AutoAI supports a number of auto-tuning capabilities, including the ability to perform "average vs. max" regression, or use default features that are commonly seen in existing machine learning models, and the ability to specify a desired learning rate. Artificial intelligence can be complex, and so an enterprise can benefit from having multiple intelligent systems. AutoAI brings together different kinds of models for a specific problem, providing insights and tuning capabilities for those models that address the particular constraints of the domain. AutoAI is composed of four modules, each having an independent use case. AutoAI "Inception" has the model training module, "Training" provides data acquisition and storage, and the tuning module. AutoAI "Synapse" has the configuration and customization module, "Configure", and the data and model pipelines module, "Pipeline", which runs the "AutoAI Customizer". AutoAI "Layers" is the compute module, which allows users to upload or import their data and then run them through AutoAI. After the creation of AutoAI, data should be gathered. Data can be gathered using a variety of data sources. AutoAI is built to work with a wide variety of sources, including open source, commercial, and both structured and unstructured data. AutoAI creates, manages, and indexes the training data used to train the models, and provides the tools needed to make those models understandable, as well as providing visualizations of their performance. AutoAI's "AutoML Inception" and "Synapse" allow users to run and manage auto-tuning as well.

Automated artificial intelligence flowchart is given in figure 1.

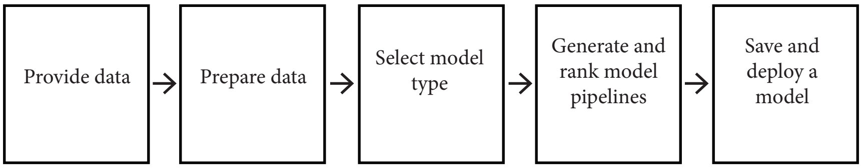

Figure 1. Automated artificial intelligence flowchart

AutoAI enables auto-tuning of predictive models for a variety of enterprise use cases, including predictive maintenance of industrial systems and industrial machines. In addition to predictive maintenance of industrial machines, AutoAI can also be used to provide predictions for these machines, help people understand what these machines are doing, and to guide the way people work. For example, AutoAI can be used to show machine performance based on operating data or system parameters, or the expected output of a predictive algorithm for a certain part of a machine. AutoAI can also be used to provide automated tuning of predictive models, or to perform remediation on models after they have been implemented. AutoAI can be used to perform comprehensive risk modeling and analysis of a company's critical assets, including whether or not to use maintenance, or what level of maintenance is appropriate, or what areas of the asset needs to be replaced. AutoAI can also be used to conduct predictive analytics on operational data or on big data in order to better identify trends, make informed business decisions, and improve operations.

5.EXAMPLE USE CASES

Automation is not limited to traditional infrastructure industry, and the implementation of technology is changing the field of construction. Even though the application of technologies in the field of civil engineering is relatively simple and there are various benefits associated with this, there are some constraints that need to be overcome before these technologies can reach their full potential. For example, there are a lot of challenges associated with the deployment of such technologies, such as the absence of specialized tools and equipment, high cost, human errors, lack of resources and other regulatory issues. The same problems also face organizations in many other industries when it comes to the adoption of AI, such as the lack of skills, the risk associated with the data lack of integration across existing IT systems, challenges associated with new regulatory requirements and shortage of investment. For the best results, companies should have the right skills and technical environment in place to successfully implement AI and machine learning technology. AI and machine learning technology are coming in as a disruptive force to all organizations, and these technologies can enhance an organization's existing abilities.

-AutoAI can be used to train "general-purpose" ML models in a range of areas, including

-Predictive maintenance of critical assets, including industrial machines

-Reporting on the historical or present status of assets or systems

-Updating/revisiting the current assets or systems

-Automating the ability to identify when new or existing assets are at risk

-Predicting when systems will fail

-Saving and using historical or current asset records in a database

-Monitoring asset health

-Metadata management

AutoAI is able to do this because it has pre-trained ML models, which can be shared or customized in order to meet a particular application's requirements. Predictive analytics can be used to improve the quality of predictions in order to reduce or eliminate the need for analysts to be involved with the models at all, as well as to more accurately understand the model's prediction. In addition, since predictions tend to be more accurate when they are derived from and monitored against the past, modeling the past is a very important part of what AutoAI can do. Additionally, since AutoAI automatically figures out which predictions are most important or useful, analysts can then be able to focus on the models that matter most to them. In some cases, auto-tuning a model is used to create a model that is better suited to what a person needs to do. For example, an analyst might want to automate work processes related to maintenance for industrial machines. Such analysis can take a lot of time and lead to incorrect conclusions, if the analyst does not have the training and experience to understand the machine, its history, and the maintenance process. When auto-tuning is used, it reduces the need for the analyst to do the analysis, and can savetime for everyone. Additional capabilities of AutoAI include the ability to automatically map models to the constraints and interfaces of a system, and the ability to cleanse the data that has been used to train the model.

The self-learning capability of AutoAI makes it possible to make changes to the underlying model without the need for an external ML library. AutoAI can be used as an end-to-end ML pipeline, from data preparation to ML training to ML inference to model selection and model deployment. Self-tuning means AutoAI can adapt to changes in the input data to improve its prediction accuracy. AutoAI can also adapt over time as it learns the unique characteristics of each data set, making it an effective tool for analytics and for getting a step closer to true self-learning. AutoAI can be trained with real-world data. It can use this training data to create a predictive model that is tailored to a particular situation. This is what makes AutoAI an effective tool for ML in industrial or engineering. Because it is run locally, AutoAI can be used in order to predict problems that are specific to a user's factory or production facility. For example, a machine might have had a recent part failure, which makes it more likely to fail in the future. AutoAI can be trained to identify the parts that are more likely to fail, which could be based on the location where the part failed or if it was kept in the machine for a long period of time. This type of deep understanding of a problem allows AutoAI to automatically pick out what parts to analyze, which can dramatically improve predictive accuracy. AutoAI has the capability to automatically create an artificial neural network based on the input data. This means a user does not need to create and train a model. Instead, AutoAI performs the task automatically. It learns the conditions of each input data set and makes its prediction with the information gatheredfrom each input data set. This is what makes it a very effective tool for analyzing large amounts of data. Automation with AutoAI not only eliminates the need for an analyst to perform the modeling work, but also makes it more productive. Instead of wasting time that could have been spent using the time to make more important analyses, AutoAI can speed up workflows and reduce the number of mistakes made. Application in civil engineering and forensic engineering has found AutoAI to be a useful tool for its workflows. Data scientists, statisticians, and industrial engineers have reported success using AutoAI for applications related to fleet management, agriculture, and machine learning. In addition, several sales organizations have been using AutoAI to automate their pipeline data preparation, so they do not have to waste time manually reviewing each data set they receive.

6.DESCRIPTION OF BOX CULVERT MODEL

The box culvert model is designed entirely of concrete. The concrete used is C30-TS500. Artificial intelligence engineering can be used in infrastructure. Box culvert attract attention in this regard. They are exposed not only to dynamic effects, but also to the effects of the fluids in them. For this reason, the box culvert model was chosen in this study. However, in this study, there is no fluid in the box culvert during the measurements. The reason for this is to keep the data volume small by using the simpler model instead of complex systems. Together with the examination of the complex models, it is planned to examine the fluid-filled culverts in this way in the future. The cross section of the model box culvert is square shaped. The height of the model box is 3 meters. The width of the model box culvert is 3 meters. The wall thickness of the model box culvert is 0.25 meters. The length of the box culvert model is 6 meters. The dimensions of the box culvert model are also given in figure 2. The three-dimensional view of the box culvert model is given in figure 3.

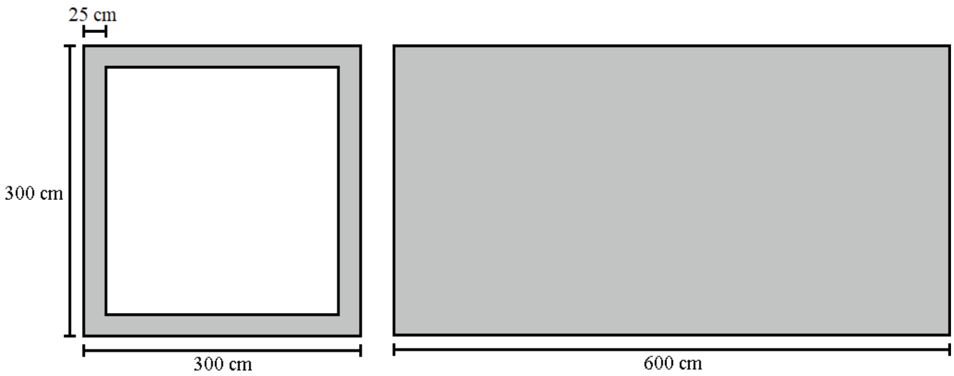

Figure 2. The dimensions of the box culvert model

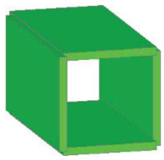

Figure 3. 3D view of the box culvert model

7.RESULTS AND DISCUSSION

MATLAB 2018b software program [20] automated artificial intelligence toolbox was used to obtain all the results. Obtained results are shared as figures.

In the figure 4 it shows the training progress of the neural network.

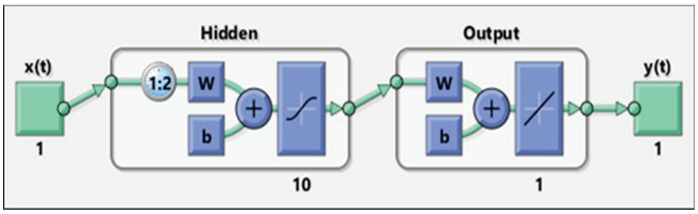

Figure 4. Neural network

process The input used in the study are given in figure 5.

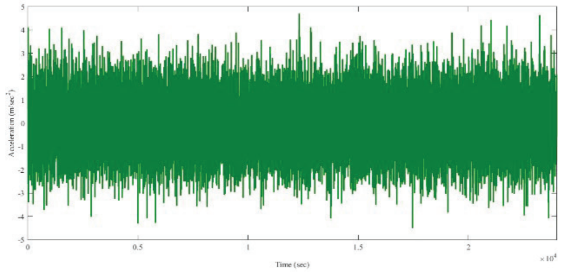

Figure 5. Input

The output used in the study are given in figure 6.

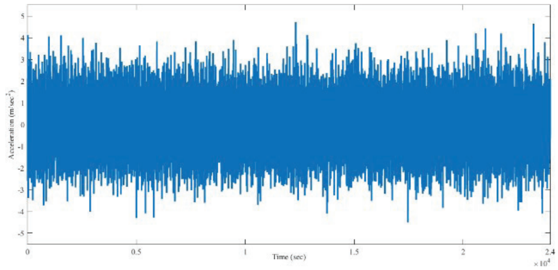

Figure 6. Output

The box culvert model's frequency obtained is given in figure 7.

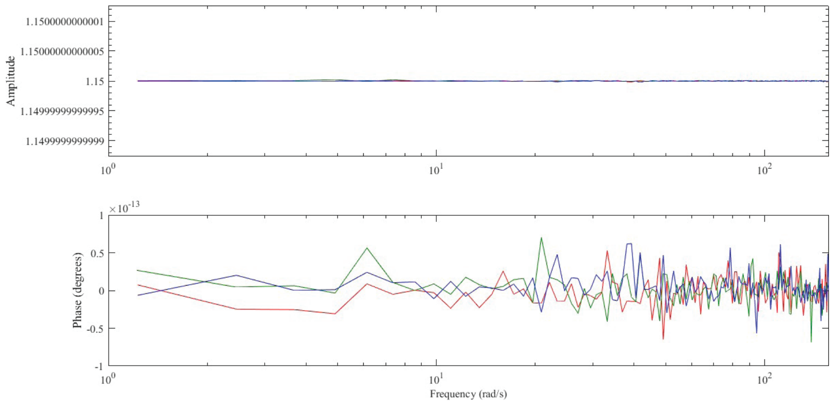

Figure 7. Frequency

The box culvert model's periodogram obtained is given in figure 8.

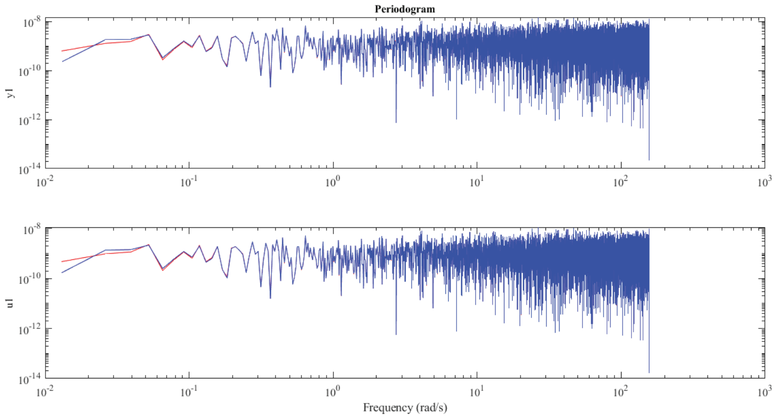

Figure 8. Periodogram

The box culvert model's poles and zeros obtained is given in figure 9.

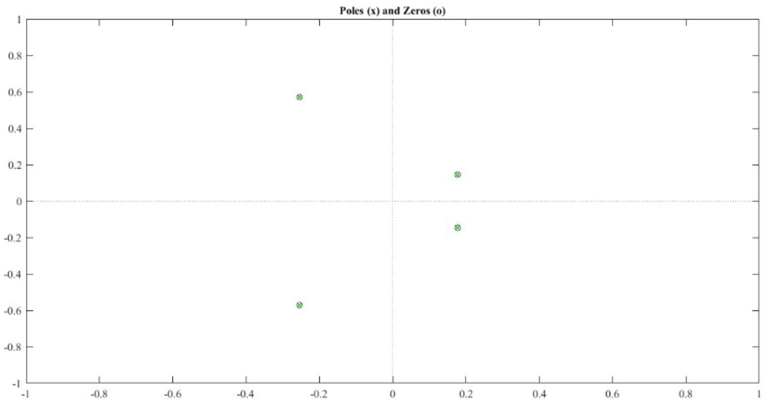

Figure 9. Poles and zeros

The box culvert model's residuals obtained is given in figure 10.

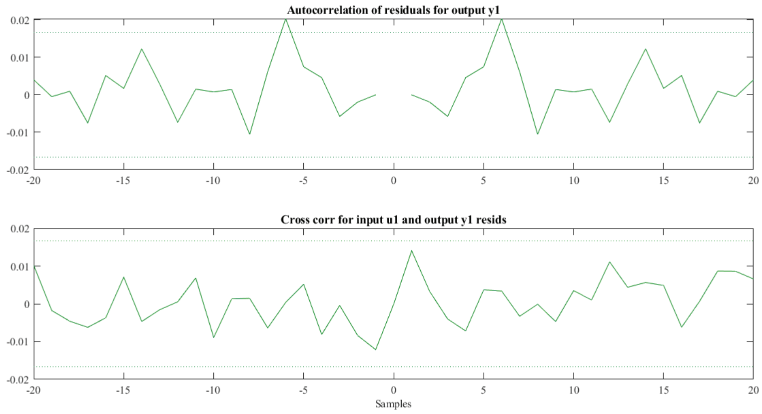

Figure 10. Residuals

The box culvert model's error histogram obtained is given in figure 11.

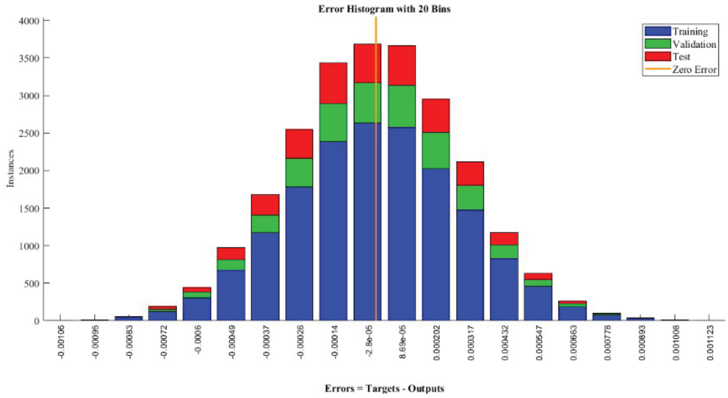

Figure 11. Error histogram

The box culvert model's response of output element obtained is given in figure 12.

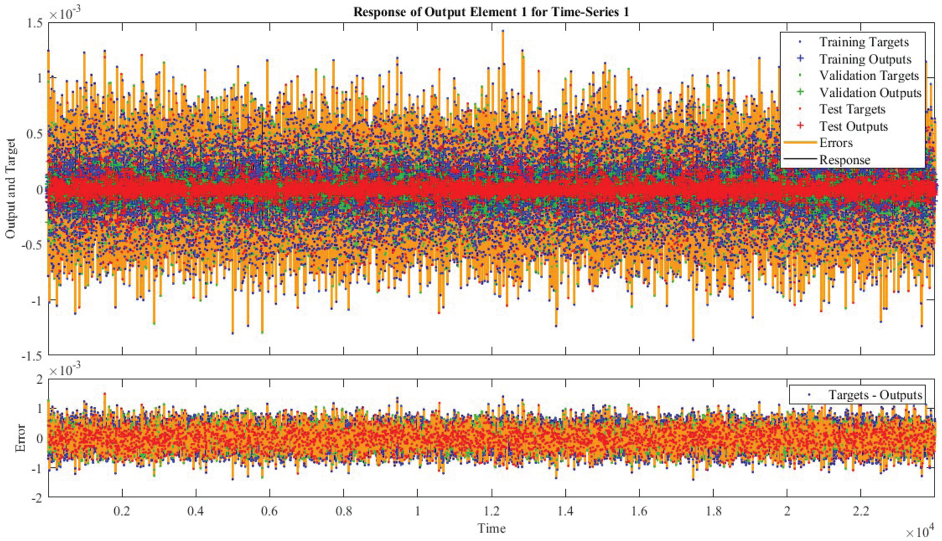

Figure 12. Response of output element

8.CONCLUSION

As a result of this study, the following graphics belonging to the box culvert model were obtained.

- The box culvert model's frequency
- The box culvert model's periodogram
- The box culvert model's poles and zeros
- The box culvert model's residuals
- The box culvert model's error histogram
- And the most important; The box culvert model's response of output

When all the findings are examined, it is seen that the automated artificial intelligence method makes very successful predictions on system identification. Thus, it is predicted that the accuracy and reliability of the data to be used in the future will increase. In addition, the processing speed and practicality of the automated artificial intelligence method attracted a lot of attention. In the light of all this information, the automated artificial intelligence application on a square shaped box culvert model was tested in terms of accuracy, practicality and utility, and successful results were clearly obtained. It is thought to be particularly successful in early warning systems against dynamic loads. In addition, it is recommended in the field of data processing and evaluation in civil engineering on the other word system identification.

REFERENCES

[1] G.F. Sirca Jr., H. Adeli, System identification in structural engineering, Scientia Iranica A (2012) 19 (6), 1355-1364

[2] J. Kim, System Identification of Civil Engineering Structures through Wireless Structural Monitoring and Subspace System Identification Methods, PhD thesis, University of Michigan, 2011.

[3] S. Tuhta and F. Günday, "MIMO System Identification of Industrial Building Using N4SID With Ambient Vibration," International Journal of Innovatıons in Engineering Research and Technology, vol. 6, no. 8, pp. 1–6, Aug. 2019.

[4] S. Tuhta, F. Günday, H. Aydin, and M. Alalou, "MIMO System Identification of Machine Foundation Using N4SID," International Journal of Interdisciplinary Innovative Research Development, vol. 4, no. 1, pp. 27– 36, Jul. 2019.

[5] S. Tuhta, F. Günday, and H. Aydin, "Subspace Identification Using N4SID Methods Applied to Model Concrete Chimney," JournalNX, vol. 6, no. 6, pp. 415–423, Jun. 2020.

[6] S. Tuhta and F. Günday, "Multi Input - Multi Output System Identification of Concrete Pavement Using N4SID," International Journal of Interdisciplinary Innovative Research Development, vol. 4, no. 1, pp. 41– 47, Jul. 2019

[7] S. Tuhta and F. Günday, "System Identification of RC Building Using N4SID," International Journal of Research and Scientific Innovation, vol. 6, no. 11, pp. 100–106, Nov. 2019.

[8] S. Tuhta, F. Günday, and M. Alalou, "Determination of System Parameters on Model Lighting Pole UsingANN by Ambient Vibration," International Journal of Research and Scientific Innovation, vol. 6, no. 11, pp. 191–195, Nov. 2019.

[9] S. Tuhta, I. Alameri, and F. Günday, "Numerical Algorithms N4SID For System Identification of Buildings," International Journal of Advanced Research in Engineering Technology Science, vol. 6, no. 1, pp. 7–15, Jan. 2019.

[10] S. Tuhta and F. Günday, "Modal Parameters Determination of Steel Benchmark Warehouse by System Identification Using ANN," International Journal of Research and Innovation in Applied Science, vol. 6, no. 12, pp. 8–12, Dec. 2019.

[11] S. Tuhta and F. Günday, "Artificial Neural Network Based System Identification Usage for Steel Sheds," International Journal of Innovations in Engineering Research and Technology, vol. 7, no. 10, pp. 22–30, Oct. 2020.

[12] S. Tuhta and F. Günday, "Dynamic Parameters Determination of Concrete Terrace Wall with System Identification Using ANN," JournalNX, vol. 6, no. 9, pp. 195–202, Sep. 2020.

[13] S. Tuhta and F. Günday, "Study for Artificial Neural Network of Aluminum Benchmark Bridge," International Journal of Research and Innovation in Applied Science, vol. 5, no. 2, pp. 90–95, Feb. 2020.

[14] S. Tuhta, F. Günday, and H. Aydin, "Nonlinear System Identification of Model Concrete Chimney Using Hammerstein Wiener Models," presented at the Global Congress of Contemporary Study a Multidisciplinary International Scientific Conference, 2020.

[15] S. Tuhta, F. Günday, and H. Aydin, "Example for Nonlinear System Identification of Model Masonry Retaining Wall with Hammerstein Wiener Models," presented at the A Multidisciplinary International Scientific Conference on Science, Technology, Education and Humanities, 2020.

[16] S. Tuhta, F. Günday, and H. Aydin, "Nonlinear System Identification of Model Concrete Chimney Using Hammerstein Wiener Models," presented at the Global Congress of Contemporary Study a Multidisciplinary International Scientific Conference, 2020.

[17] S. Tuhta, F. Günday, and H. Aydin, "System Identification of Model Steel Bridge with Genetic Algorithms," International Journal of Research and Innovation in Applied Science, vol. 5, no. 1, pp. 55–59, Jan. 2020.

[18] S. Tuhta, F. Günday, and H. Aydin, "System Identification of Model Steel Bridge with Fuzzy Logic," International Journal of Research and Innovation in Applied Science, vol. 5, no. 1, pp. 50–54, Jan. 2020.

[19] S. Tuhta, F. Günday, and A. Alihassan, "System Identification of Model Steel Chimney with Fuzzy Logic," International Journal of Research and Innovation in Applied Science, vol. 5, no. 1, pp. 11–15, 2020.

[20] MATLAB and Statistics Toolbox Release 2018b, the Math Works, Inc., Natick, Massachusetts, United States.